Keypoint Transfer Segmentation

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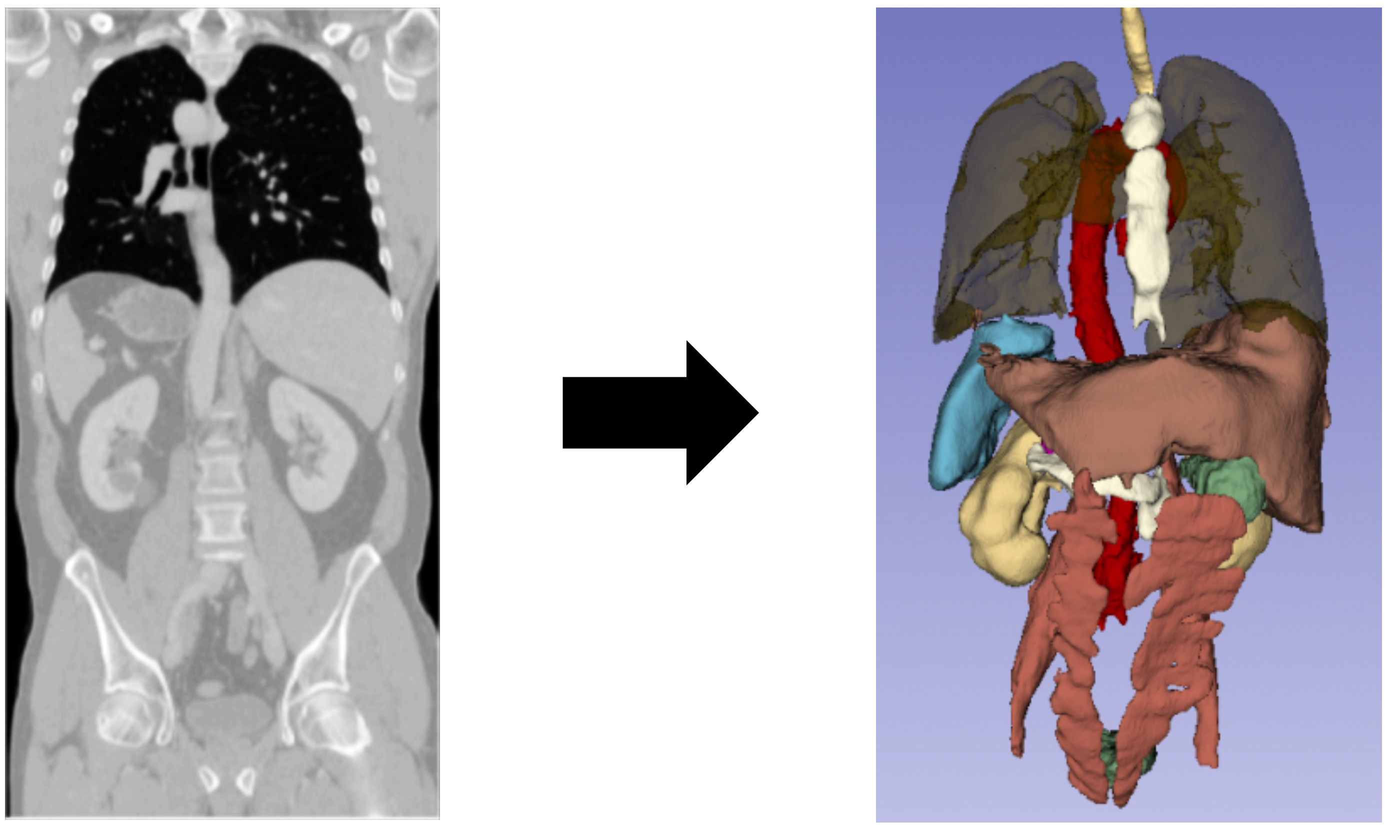
W. Wells, P. Golland

Whole-Body Segmentation

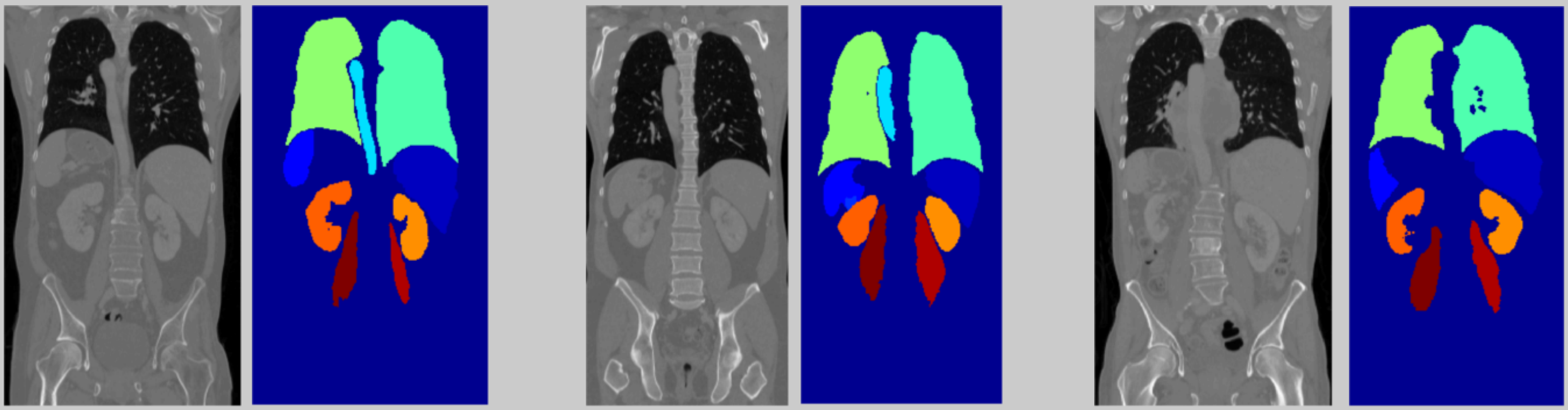
- Large field of view, large image matrix

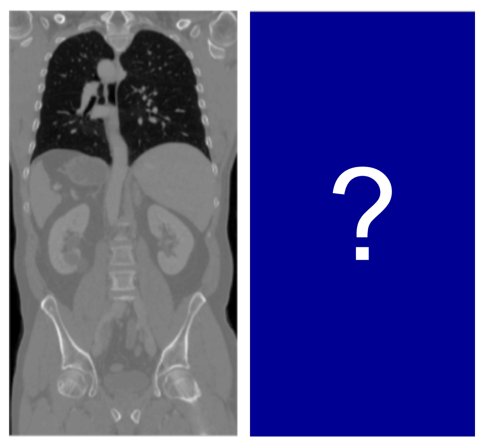


Source: visceral.eu

Keypoint Transfer Segmentation

Training Images and Segmentations

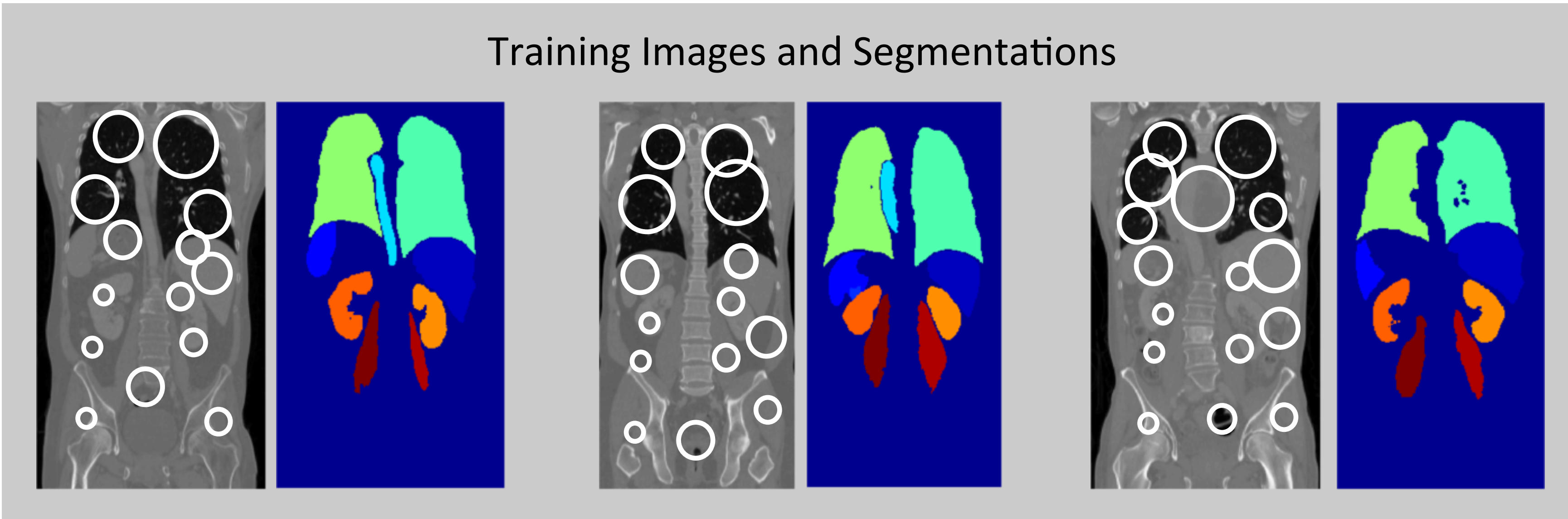


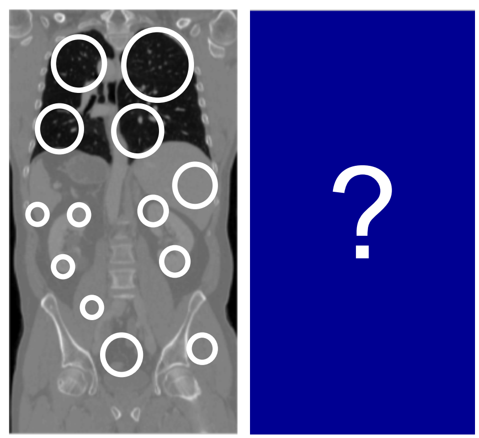


Test Image

Steps:
1. Extraction
2. Matching
3. Voting
4. Segmentation

Keypoint Transfer Segmentation



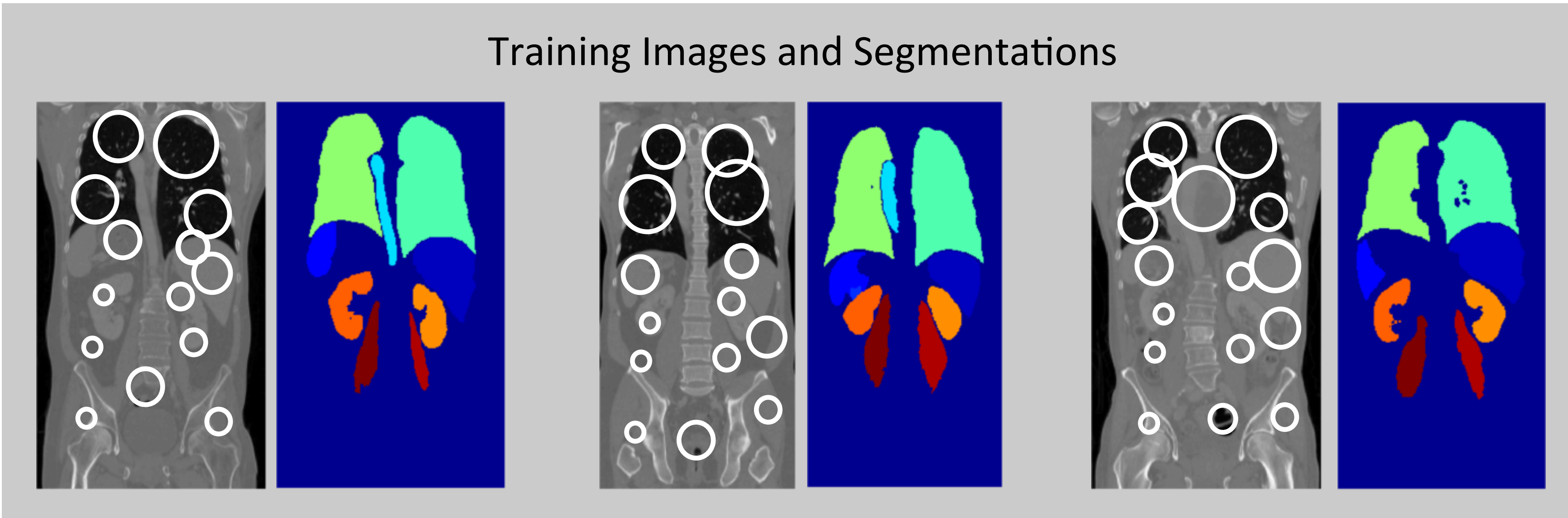


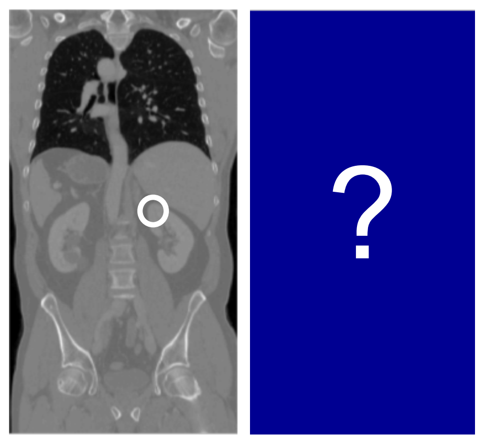
Test Image

Steps:

1. **Extraction**
2. Matching
3. Voting
4. Segmentation

Keypoint Transfer Segmentation





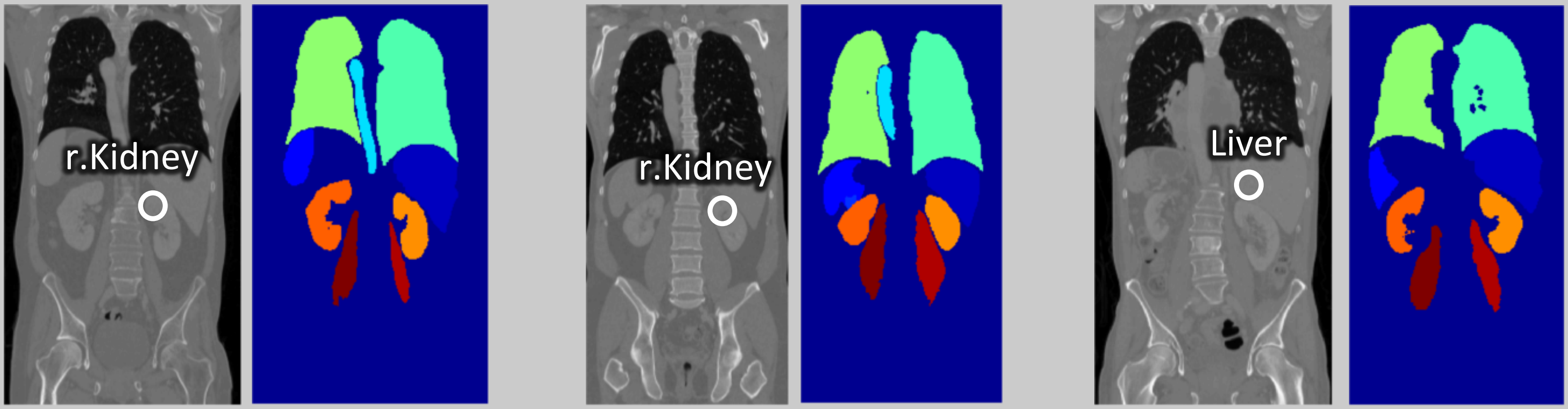
Test Image

Steps:

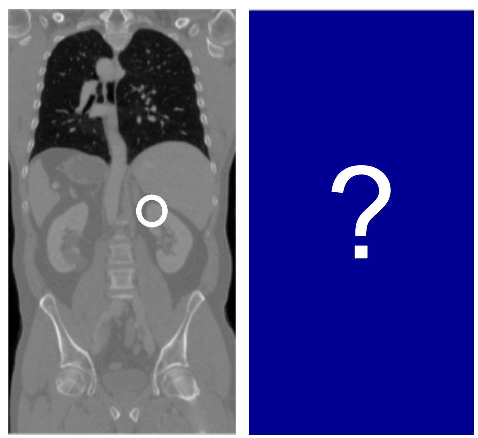
1. Extraction
2. **Matching**
3. Voting
4. Segmentation

Keypoint Transfer Segmentation

Training Images and Segmentations



<u>Votes:</u>
- r.Kidney
- r.Kidney
- Liver



Test Image

Steps:
1. Extraction
2. Matching
3. **Voting**
4. Segmentation

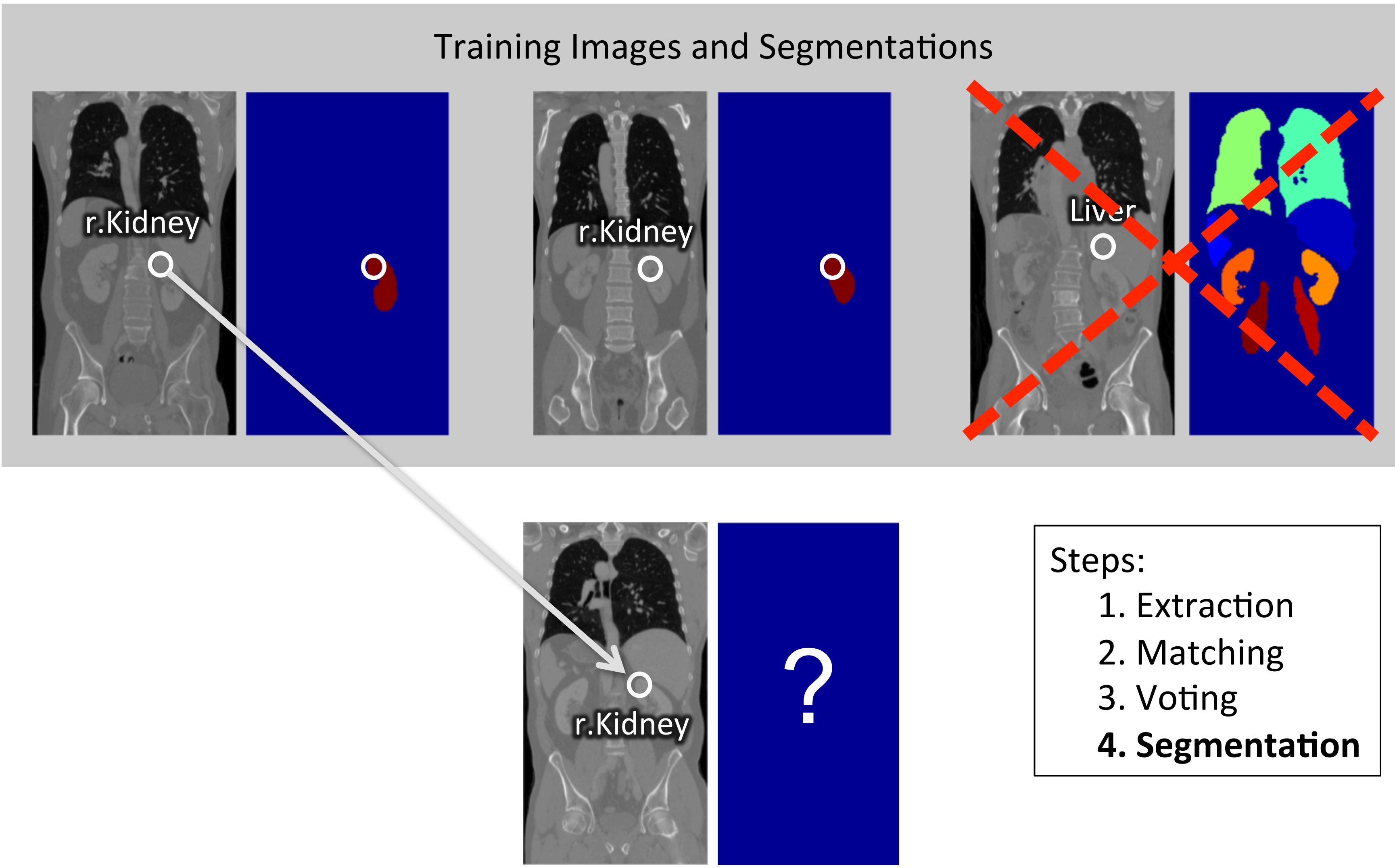
Keypoint Transfer Segmentation

Votes:
- **r.Kidney**
- **r.Kidney**
- Liver

Test Image

Steps:
1. Extraction
2. Matching
3. **Voting**
4. Segmentation

Keypoint Transfer Segmentation

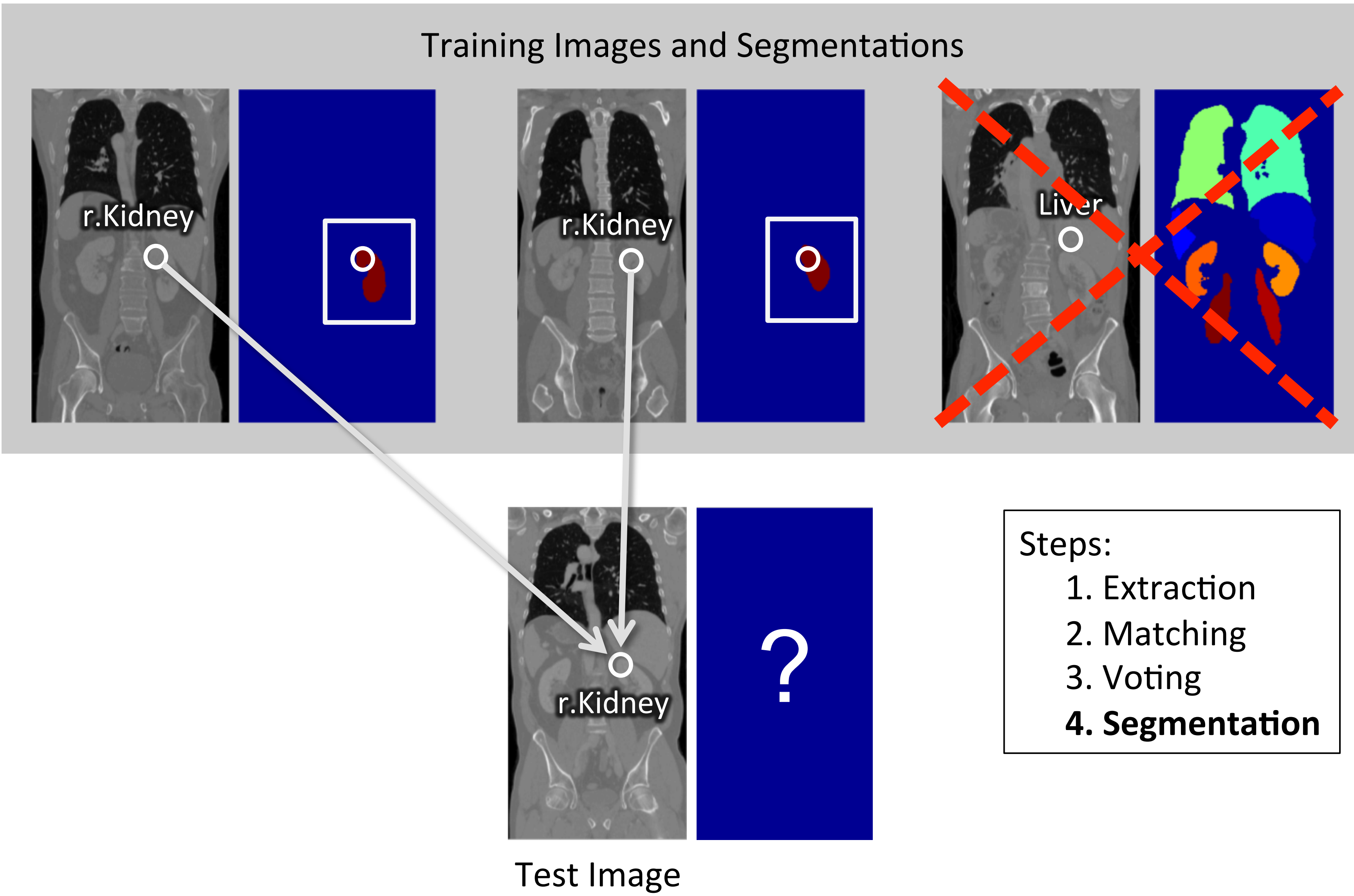


Test Image

Steps:

1. Extraction
2. Matching
3. Voting
4. **Segmentation**

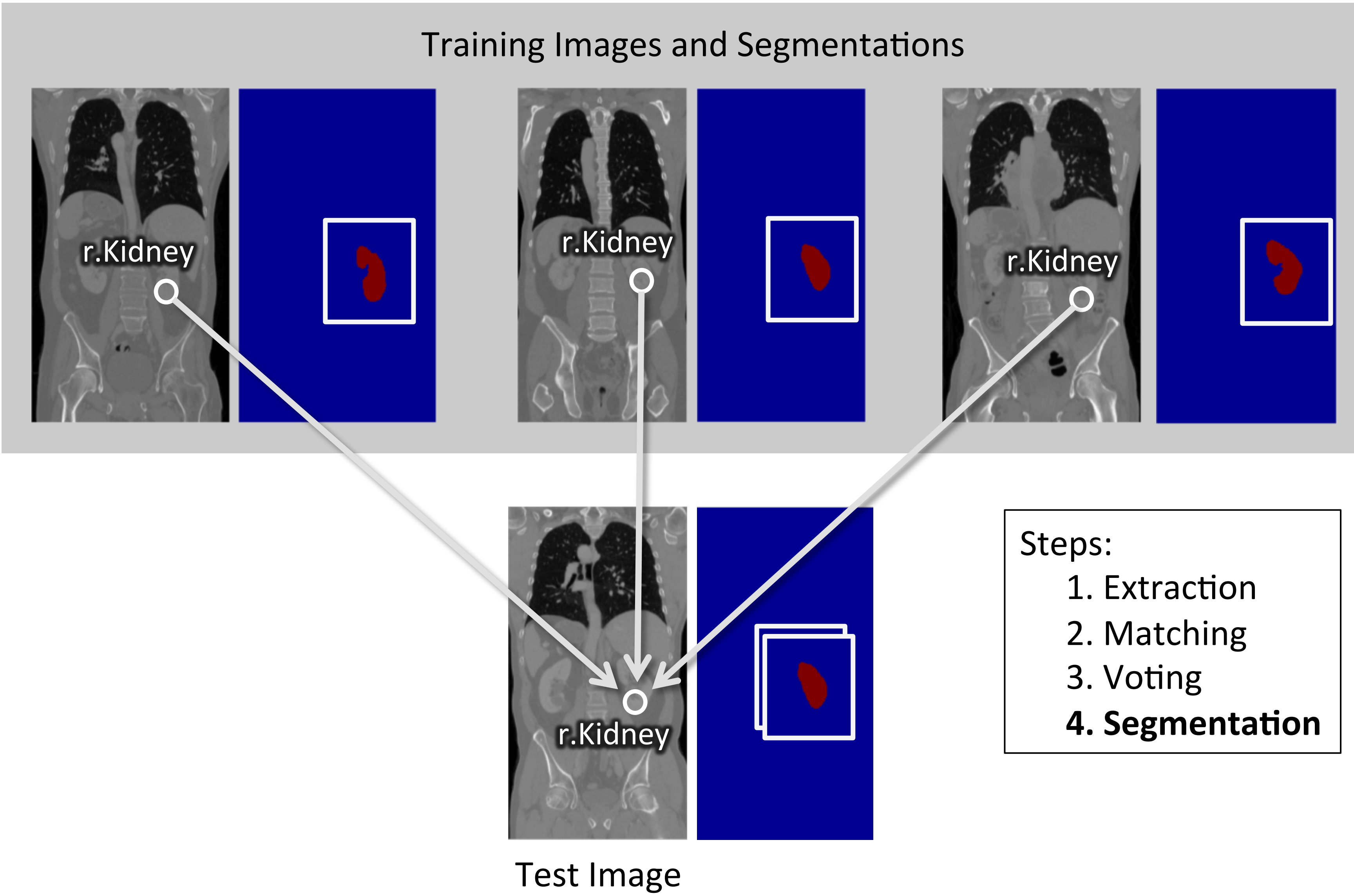
Keypoint Transfer Segmentation



Steps:

1. Extraction
2. Matching
3. Voting
4. **Segmentation**

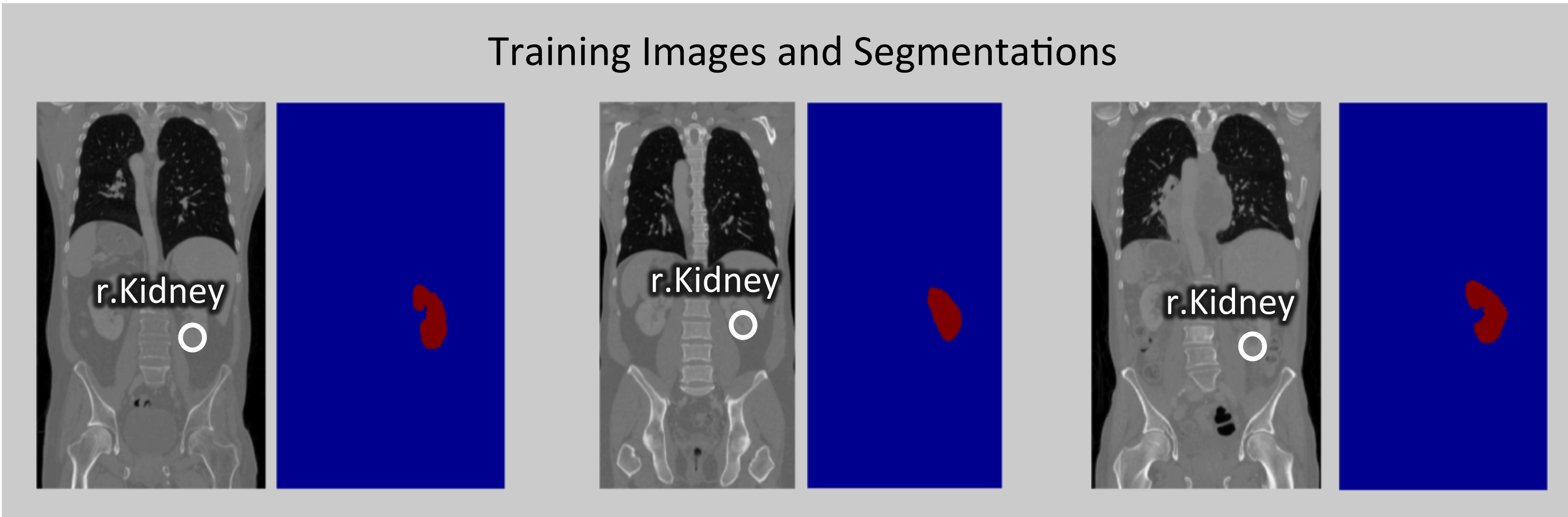
Keypoint Transfer Segmentation

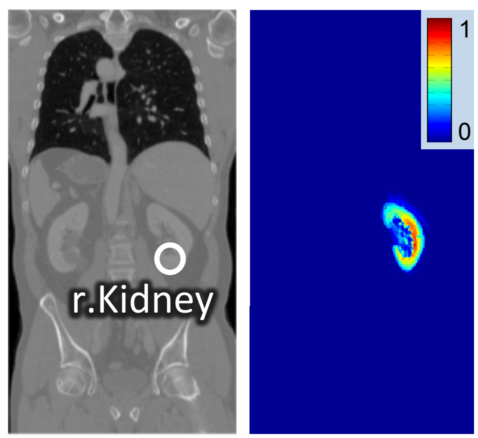


Steps:

1. Extraction
2. Matching
3. Voting
4. **Segmentation**

Keypoint Transfer Segmentation



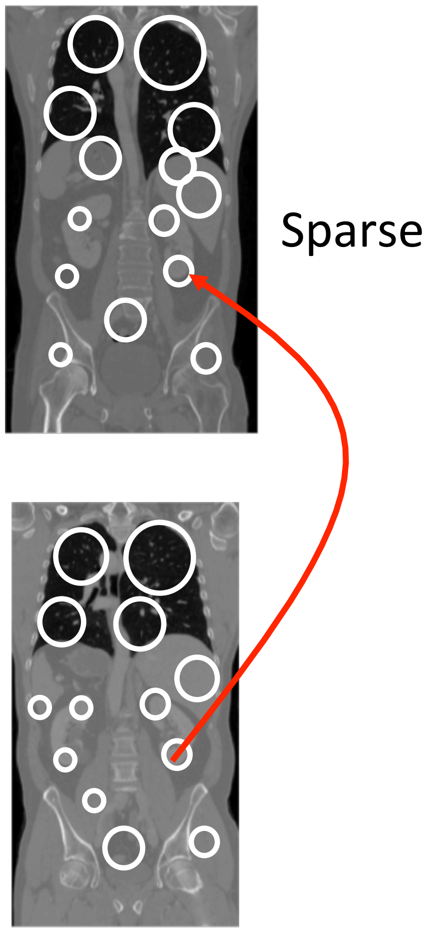


Test Image

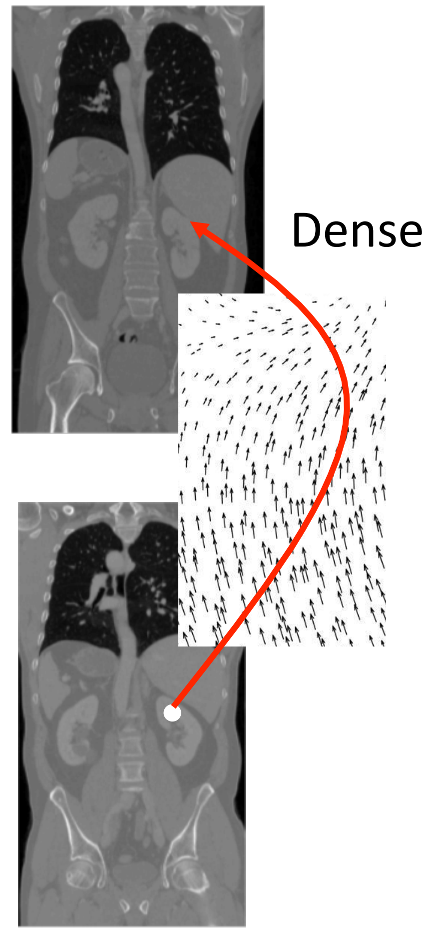
Steps:
1. Extraction
2. Matching
3. Voting
4. **Segmentation**

Difference to state-of-the-art: Sparse Correspondences

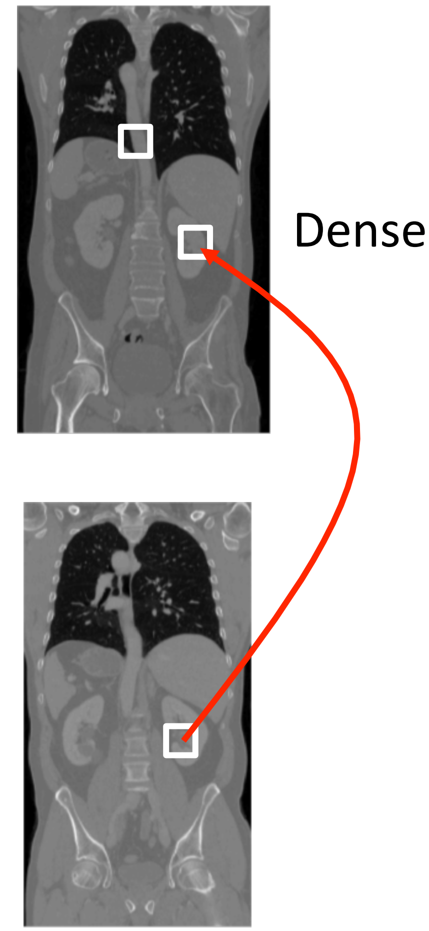
Keypoint Transfer



Registration-Based



Patch-Based (NLM)



Related Work

- Segmenting large field-of-view scans
  - Entangled Decision Forests (Montillo, IPMI 2011)
  - Discriminative / Generative Model (Iglesias, IPMI 2011)
  - Local / Global Context (Lay, IPMI 2013)

- Organ Detection
  - Marginal Space Learning (Zheng, IPMI 2009)
  - Regression Forests (Criminisi, MedIA 2013)

Require a training stage.

Related Work

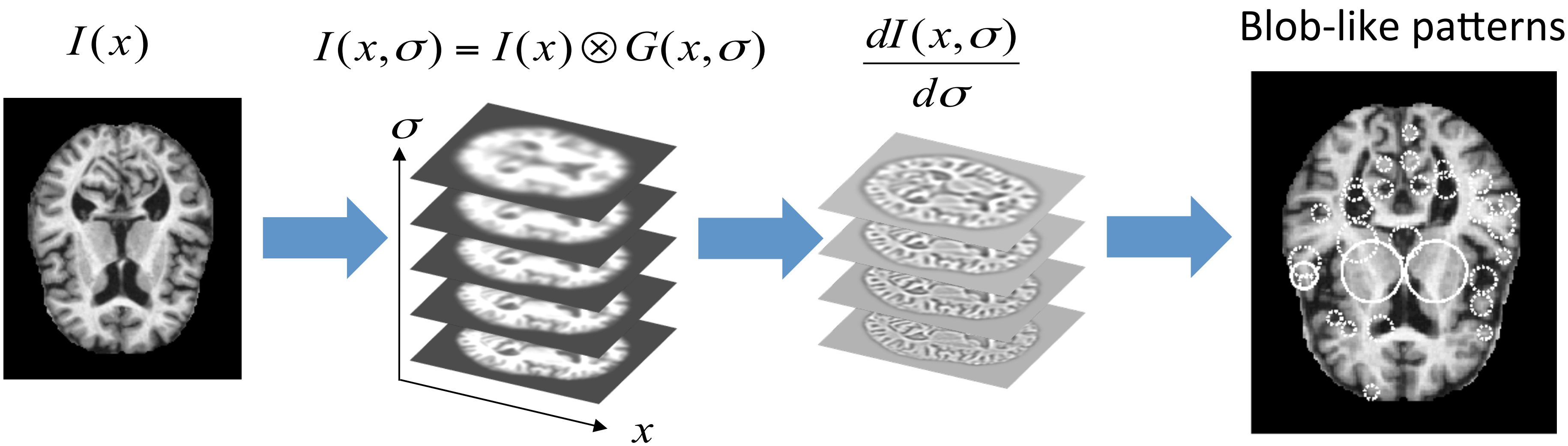
- Data
  - VISCERAL Challenge (Langs, 2013; Del Toro, 2014)
  - Multi-atlas segmentation
    - Del Toro, ISBI challenge, 2014
    - Goksel, ISBI challenge,2014
- Keypoints – 3D SIFT
  - Image alignment (Toews, IPMI 2013, MedIA 2013)
  - NeuroImaging (Toews, NeuroImage 2010)
  - Big data analysis (Poster #7)

Method

1. Keypoint extraction
2. Matching
3. Voting
4. Segmentation

Keypoint Detection

- Difference-of-Gaussian scale-space extrema



$$\{(x_i, \sigma_i)\} = \text{local} \max_{x,\sigma} \left| \frac{dI(x,\sigma)}{d\sigma} \right|$$

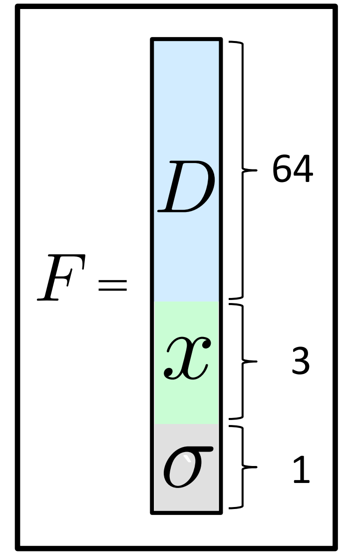
x : Location

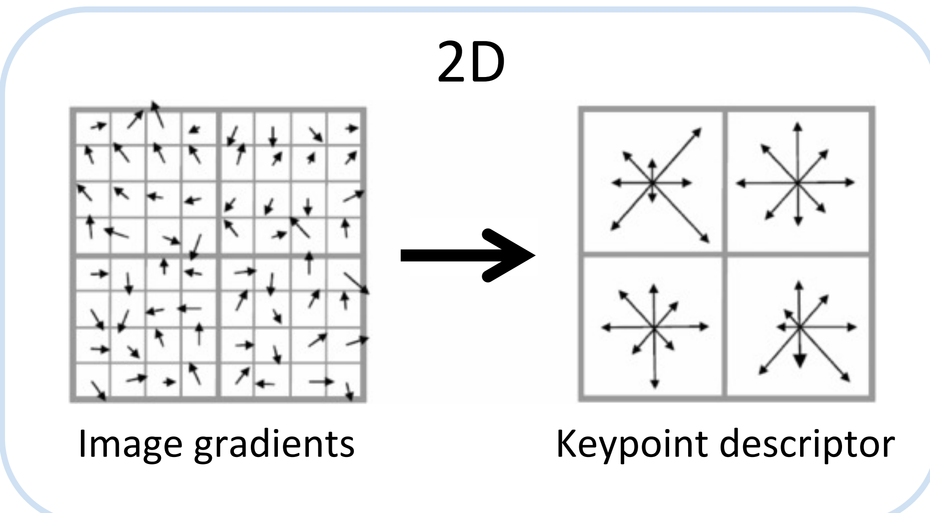
σ : Scale

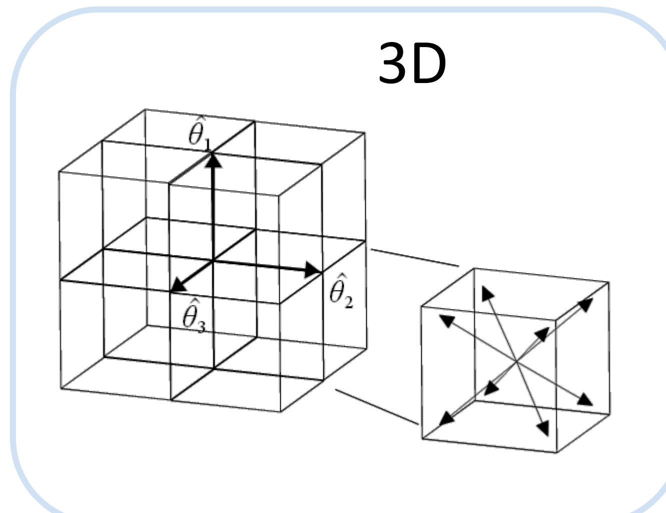
Toews et al., 2013

Keypoint Description

- Encode local image content
- Gradient orientation histogram (GoH)
  - Quantization: 8 blocks x 8 orientation bins







Toews et al., 2013

Keypoint Matching

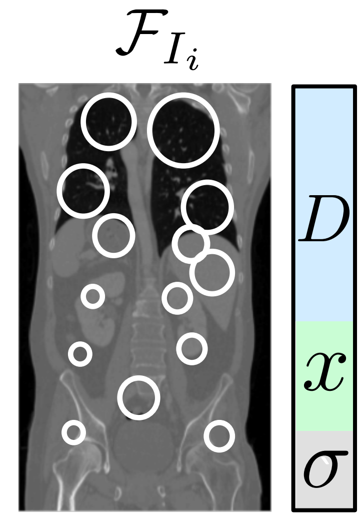
- Find nearest neighbors

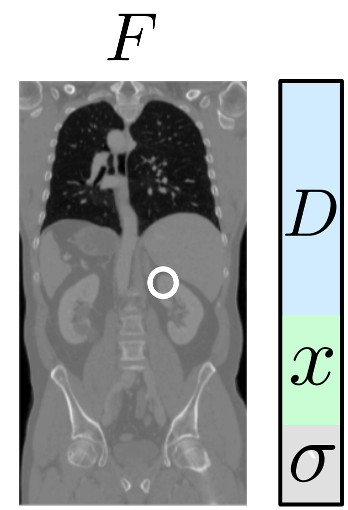
$$\underset{\mathcal{F}\in\mathcal{F}_{I_i}}{\text{minimize}} \quad \|F^D - \mathcal{F}^D\|$$

$$\text{subject to} \quad \varepsilon_\sigma^{-1} \leq \frac{F^\sigma}{\mathcal{F}^\sigma} \leq \varepsilon_\sigma$$

$$\varepsilon_\sigma = 2$$

- Estimate global translation t_i





Keypoint Matching

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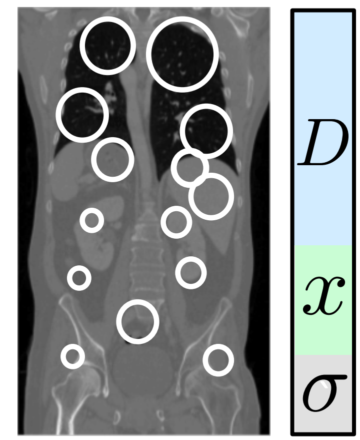
$$\text{subject to} \quad \varepsilon_\sigma^{-1} \leq \frac{F^\sigma}{\mathcal{F}^\sigma} \leq \varepsilon_\sigma,$$

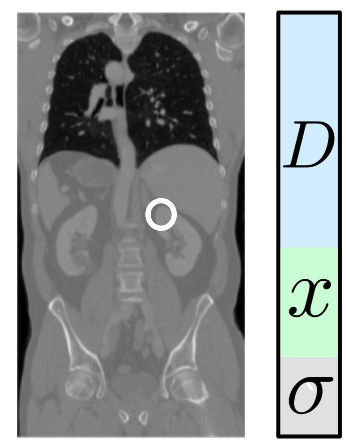
$$\|F^x - \mathcal{F}^{x+t_i}\|_2 < \varepsilon_x$$

ε_x: keep 10% of closest matches

$\mathcal{F}_{I_i}$

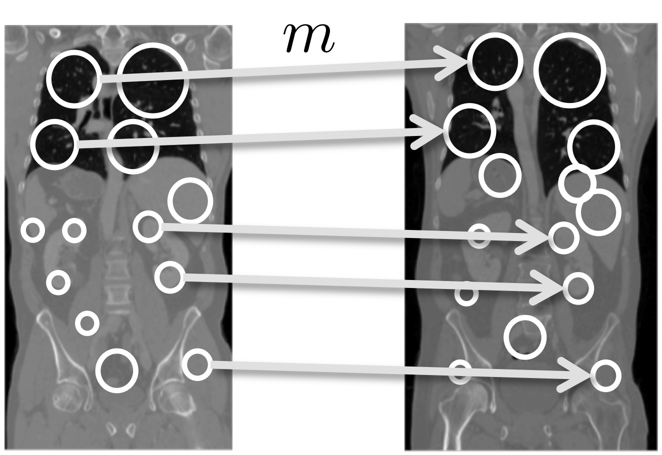


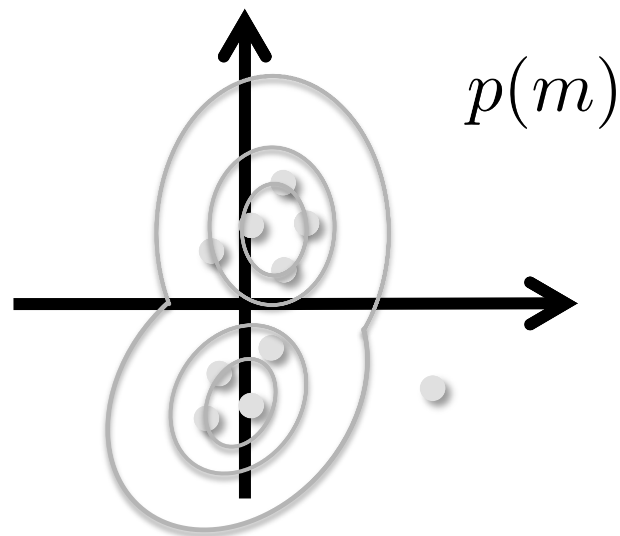
F



Distribution Over Matches

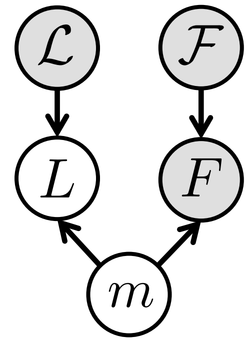
- Consistency of matches between two images

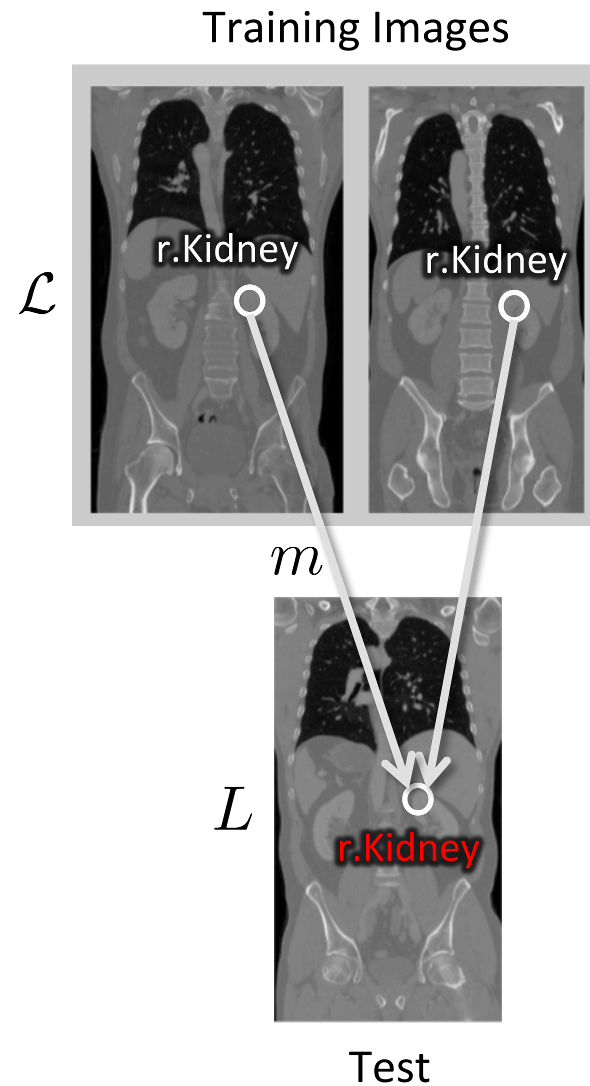




Kernel Density Estimation

Keypoint Voting





Estimate label of keypoint L

$$p(L, F, \mathcal{L}, \mathcal{F}) = \sum_{m \in \mathcal{M}(F)} p(L, F, \mathcal{L}, \mathcal{F}, m)$$

$$= \sum_{m \in \mathcal{M}(F)} p(L|\mathcal{L}, m) \cdot p(F|\mathcal{F}, m) \cdot p(m)$$

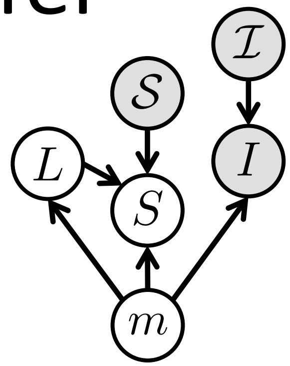
$$p(L = l|\mathcal{L}, m) = \begin{cases} 1 & \text{if } \mathcal{L}_{m(F)} = l, \\ 0 & \text{otherwise} \end{cases}$$

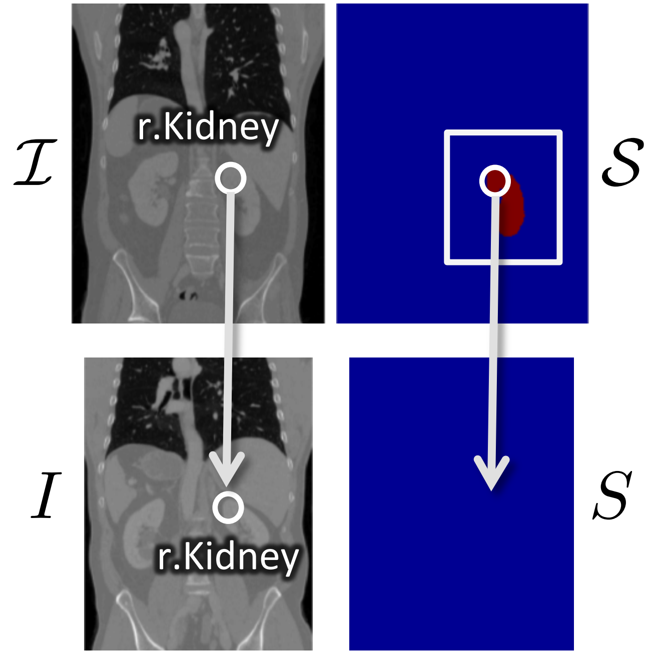
$$p(F|\mathcal{F}, m) = \frac{1}{\sqrt{2\pi\tau^2}} \exp\left(-\frac{\|F^D - \mathcal{F}^D_{m(F)}\|_2^2}{2\tau^2}\right)$$

$$\hat{L} = \arg\max_{l \in \{1,\ldots,\eta\}} p(L = l, F, \mathcal{L}, \mathcal{F})$$

Segmentation Transfer

Infer segmentation S





$$p(S, I, \mathcal{S}, \mathcal{I}, \mathcal{L}) = \sum_{m \in \mathcal{M}} \sum_{L} p(S, I, \mathcal{S}, \mathcal{I}, \mathcal{L}, L, m)$$

$$= \sum_{m \in \mathcal{M}} \sum_{L} p(S|L, \mathcal{S}, m) \cdot p(I|\mathcal{I}, m) \cdot p(L|m) \cdot p(m)$$

$$p(S|L, \mathcal{S}, m) \propto \begin{cases} 1 & \text{if } S^L = \mathcal{S}^L_m, \\ 0 & \text{otherwise} \end{cases}$$

$$p(I(x)|\mathcal{I}, m) = \frac{1}{\sqrt{2\pi\nu}} \exp\left(-\frac{(I(x) - \mathcal{I}_m(x))^2}{2\nu^2}\right)$$

$$p(L|m) \propto p(L) \cdot \delta(\mathcal{L}_m, \hat{L})$$

Estimate segmentation

$$\hat{S}(x) = \underset{l \in \{1, \ldots, \eta\}}{\arg\max}\ p(S(x) = l)$$

Background for less than 15%

No improvement with organ-wide affine transformation

Experiments

- VISICERAL (re-sampled to 2mm)
  - 20 contrast-enhanced CT (ceCT), 200 x 200 x 349
  - 20 whole-body CT (wbCT), 217 x 217 x 695
  - 10 organs
- Leave-one-out procedure
- Comparison to multi-atlas segmentation
  - Majority Voting
  - Locally-weighted voting (Sabuncu, TMI 2010)
  - Deformable registration: ANTS (Avants, 2008)

Keypoint Voting Statistics

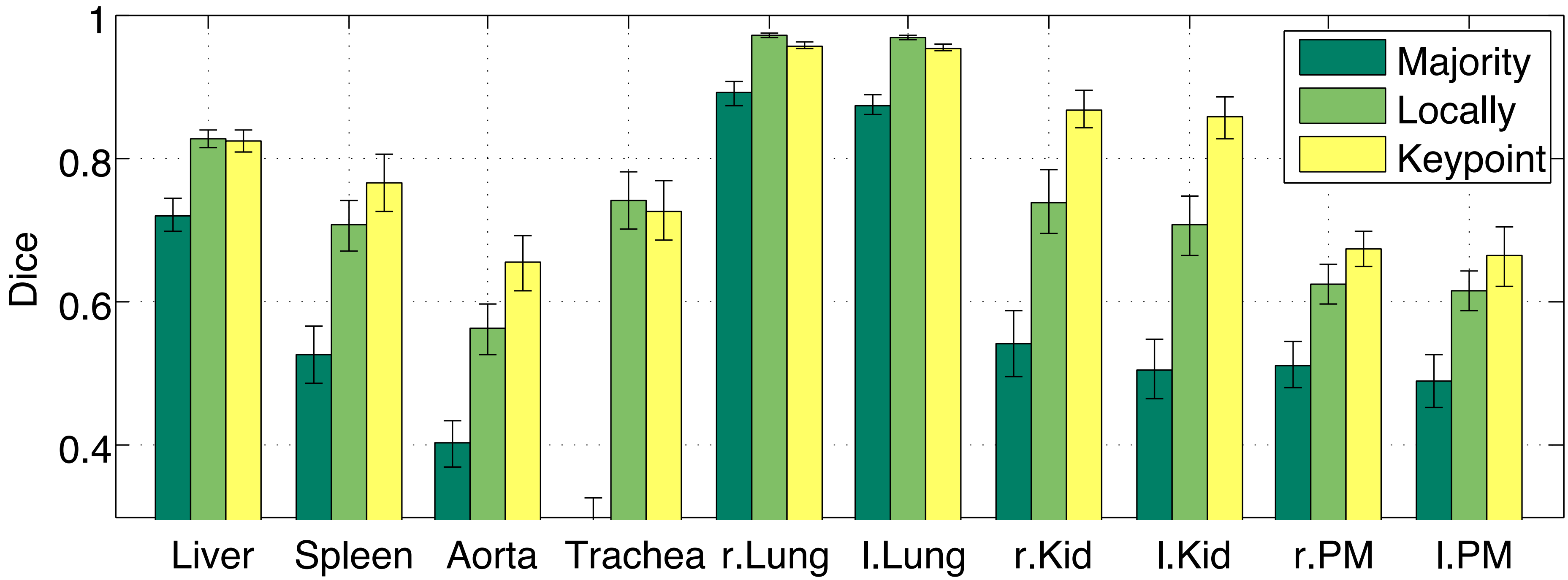
Contrast enhanced CT

Organs	Liver	Spleen	Aorta	Trachea	r.Lung	l.Lung	r.Kid	l.Kid	r.PM	l.PM	Bckgrnd
# Keypts	13.6	4.0	7.6	3.0	29.7	24.7	12.1	12.2	2.5	3.0	526.0
% Labeled	73	89	98	100	95	92	98	99	94	92	33
% Correct	87	91	97	99	100	100	98	100	99	93	0

No background keypoints in training set

Segmentation Accuracy

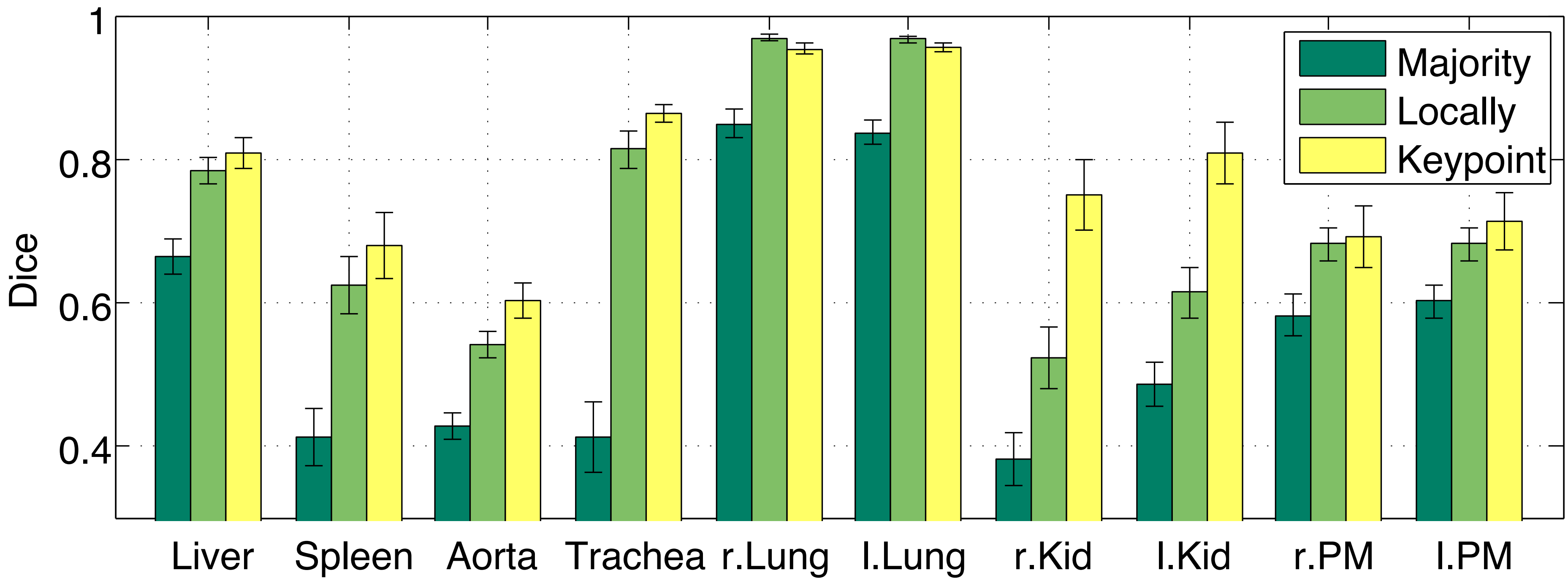
Contrast enhanced CT



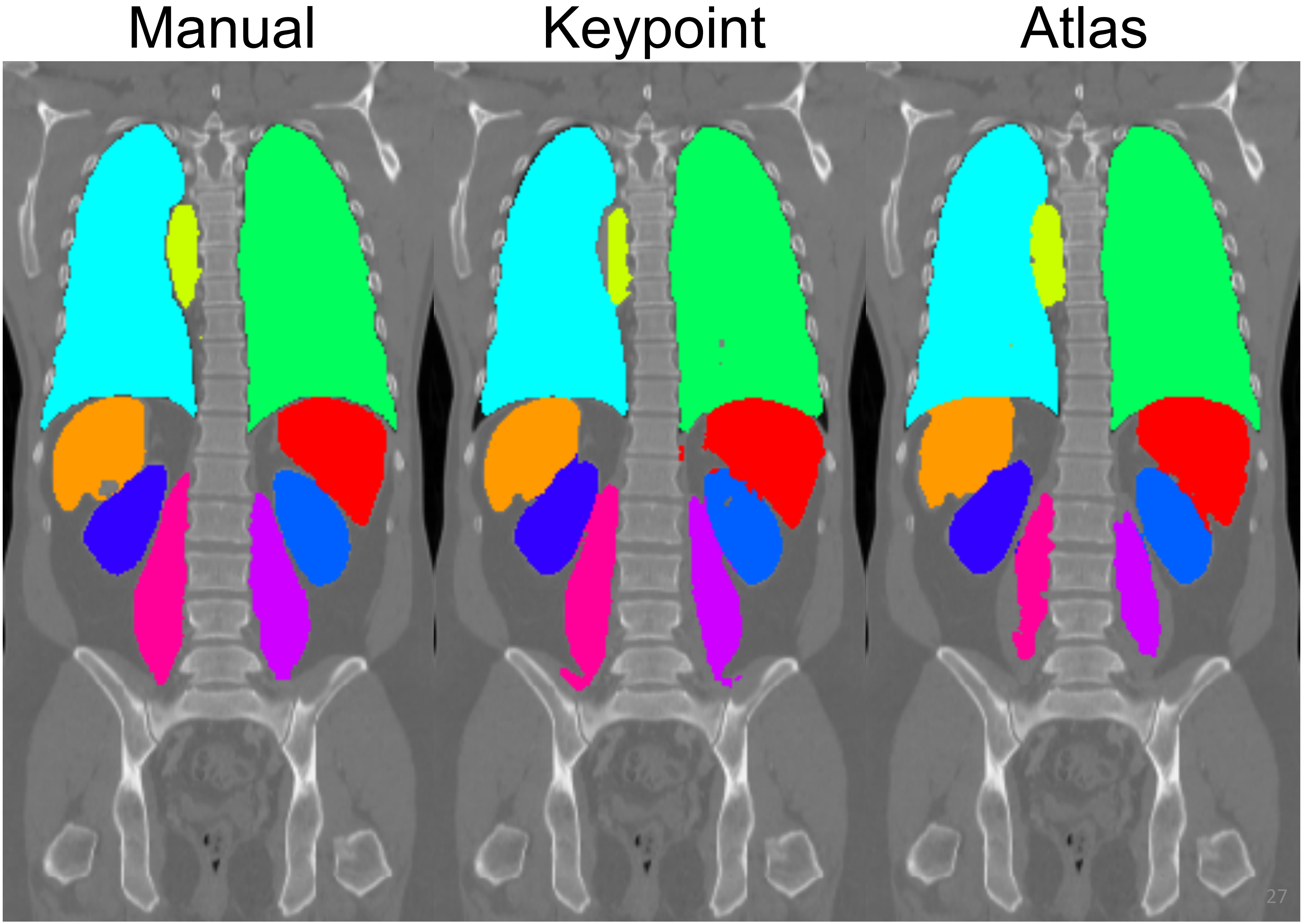
Bars: Mean
Error bars: standard error

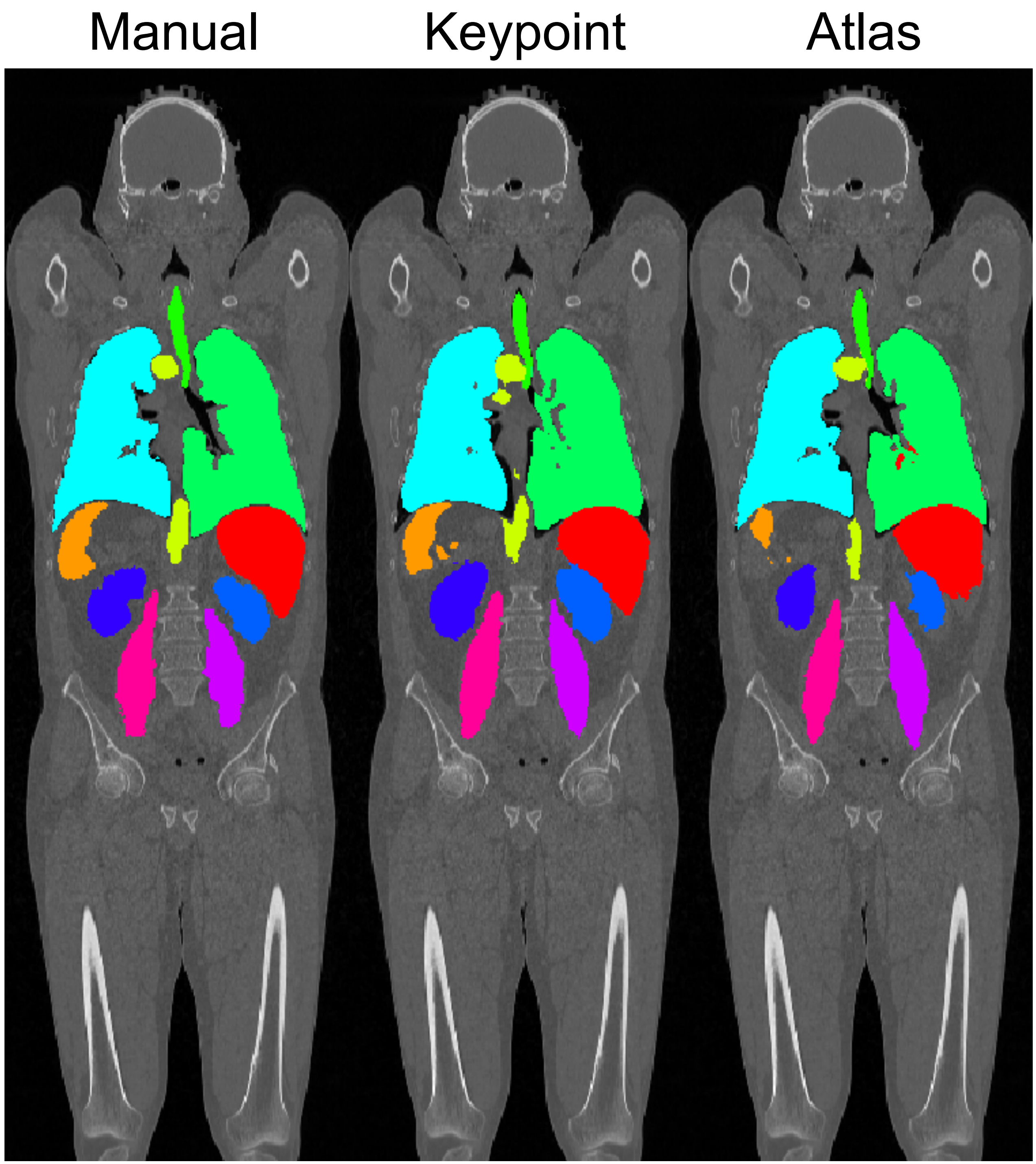
Segmentation Accuracy

Whole-body CT

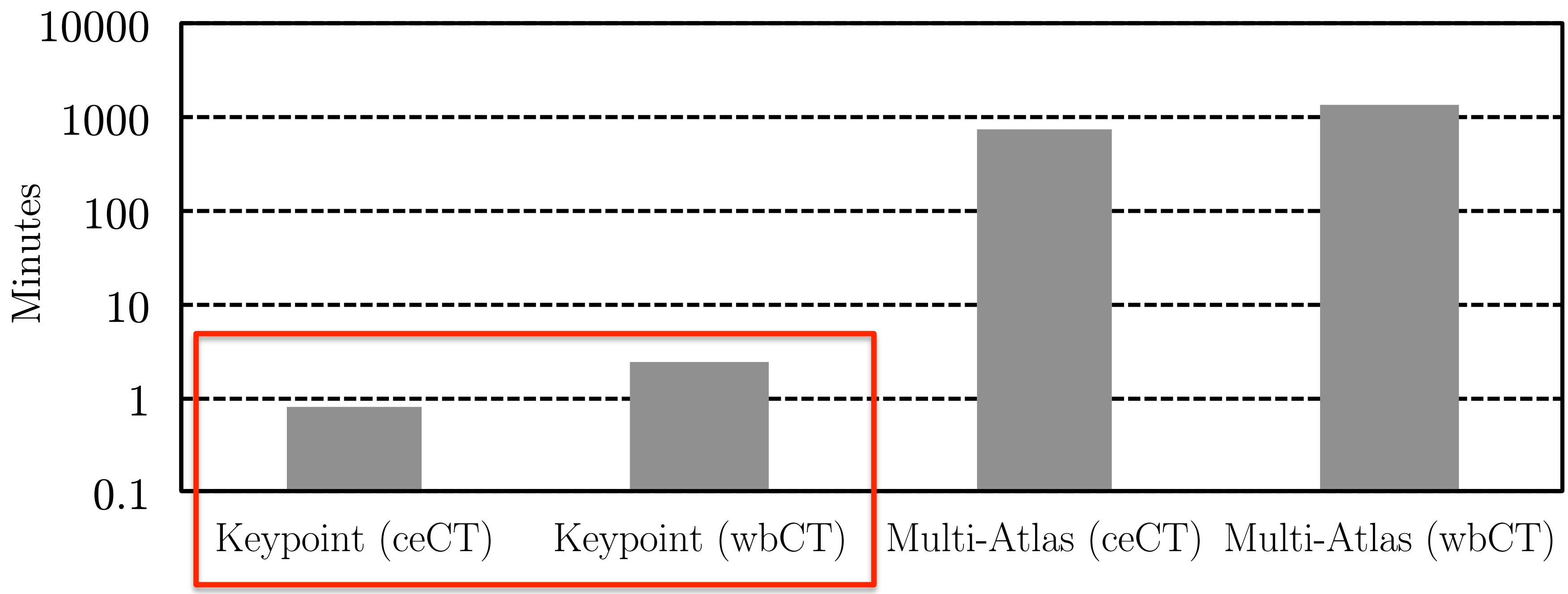


Bars: Mean
Error bars: standard error


Manual
Keypoint
Atlas

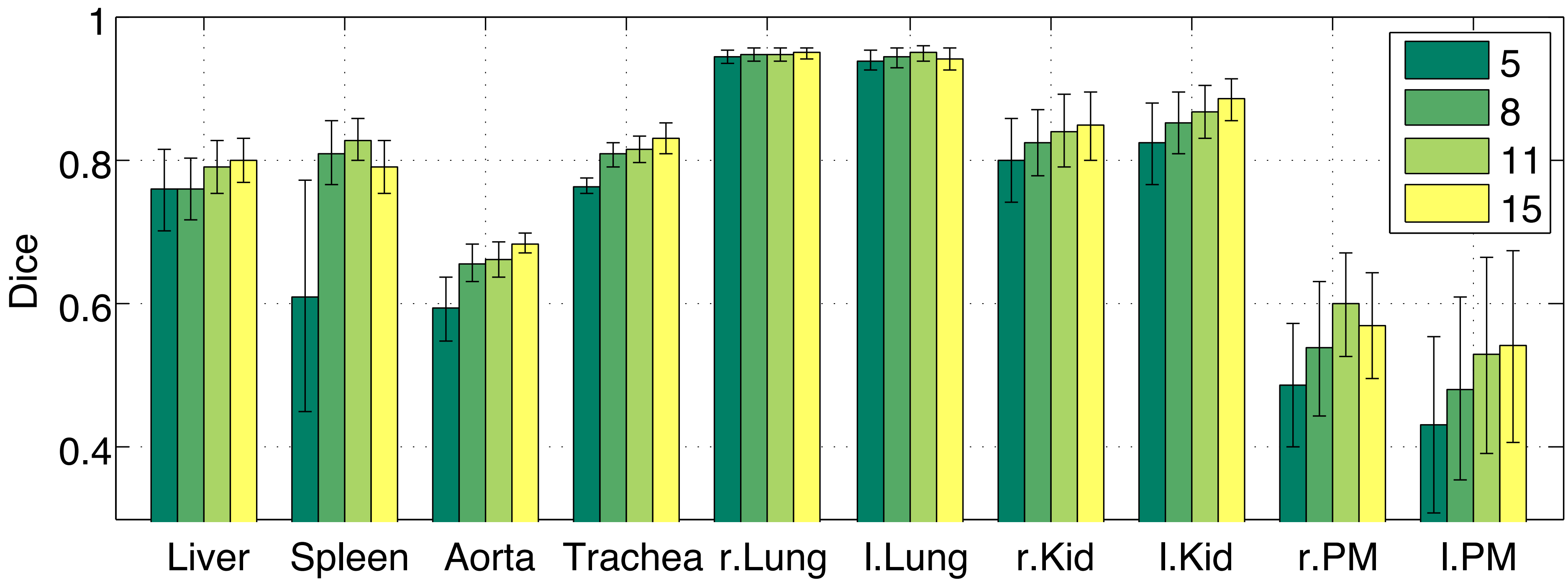

Manual
Keypoint
Atlas

Runtime


10000
1000
100
10
1
0.1
Minutes
Keypoint (ceCT)
Keypoint (wbCT)
Multi-Atlas (ceCT)
Multi-Atlas (wbCT)

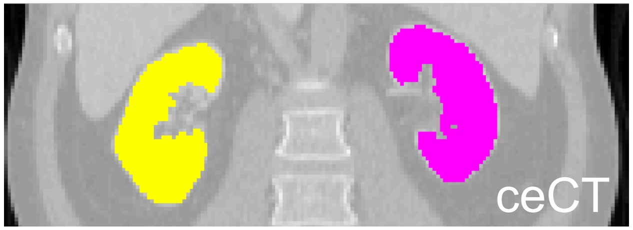
Segmentation Accuracy

Vary number of training images

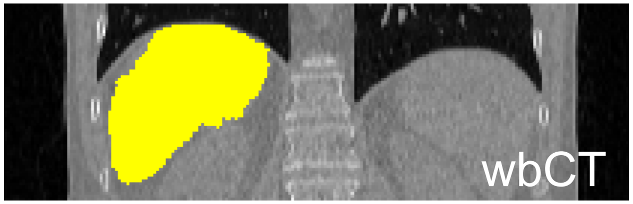


Limited Field-of-View

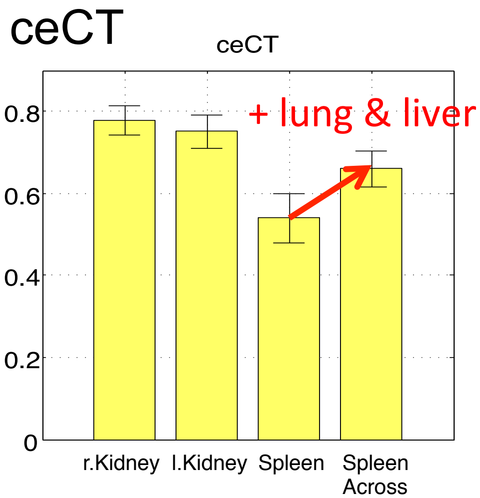
- Kidneys

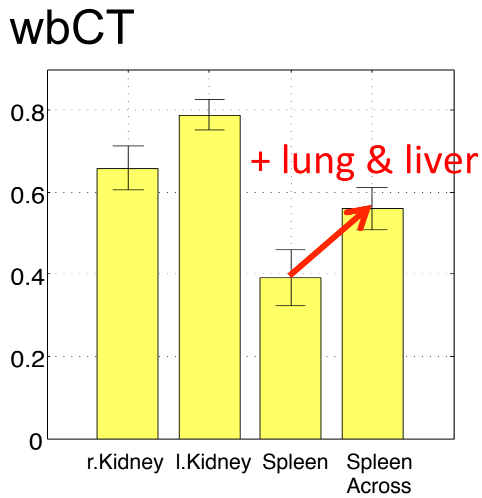


- Spleen



- Out of the box registration fails
- Add neighboring keypoints to vote for spleen





Funding Sources

- Humboldt foundation
- National Alliance for Medical Image Computing (U54-EB005149)
- NeuroImaging Analysis Center (P41-EB015902)
- Wistron Corporation

Conclusions

- Keypoint transfer segmentation
  - Maps entire organs
  - Sparse correspondences
- Generative models for inferring labels and segmentation
- Characteristics
  - Robust to variations in field-of-view
  - Computationally efficient